

AUTOMATIC DETECTION OF SLEEP STAGES USING THE EEG

P. Van Hese,^{1,2} W. Philips,³ J. De Koninck,⁴ R. Van de Walle,¹ and I. Lemahieu¹

¹Elis Department, MEDISIP, IBITECH, Ghent University, Belgium

²Department of Neurology, Ghent University Hospital, Belgium

³Telin Department, Ghent University, Belgium

⁴Department of Neurology, St.-Vincentius Hospital, Deinze, Belgium

e-mail: peter.vanhese@rug.ac.be, Tel. +32-9-240.45.47, Fax. +32-9-240.49.71

ABSTRACT

We present a method for the detection of sleep stages using the EEG (electroencephalogram). The method consists of four steps: segmentation; parameter extraction; cluster analysis; and classification. The parameters we compared were the parameters of Hjorth, the harmonic parameters and the relative band energy. For cluster analysis we used a modified version of the K-means algorithm. It is shown that the investigated parameters are capable of extracting information from the EEG relevant for sleep stage scoring. Using the modified K-means algorithm it is possible to find 'similar' segments and hence automate the detection of sleep stages. However, extra information e.g., the ECG (electrocardiogram) or the EOG (electrooculogram) is probably necessary for a clear discrimination between the different sleep stages. **Keywords:** automatic sleep scoring, EEG analysis

1. INTRODUCTION

An EEG (electroencephalogram), a measurement of the time-varying potential differences between electrodes fixed on the scalp, is an important clinical aid used by the neurologist for the diagnosis of sleep disorders. Sleep is a non-uniform biological state and can be divided into 2 main types: rapid eye movement (REM) and non-rapid eye movement (NREM) sleep. The latter is subdivided into stages 1, 2, 3 and 4 according to the current sleep scoring standard proposed by Rechtschaffen and Kales [1].

A review of the EEG can reveal unusual patterns. However, a complete visual inspection of a long-term EEG recording is a time-consuming and difficult task. So, a method to facilitate the review would be highly appreciated. In the past a number of automated sleep stage scoring methods were proposed based on EEG records, sometimes in combination with the EOG (electrooculogram) and the EMG (electromyogram) [2,3]. These methods have in common that they extract certain features from the recordings and apply a number of rules to classify these segments into one of the 5 sleep stages.

We present a method that uses a number of time and frequency domain parameters obtained from a segmented sleep EEG recording to construct a vector space. By using a slightly modified version of the K-means algorithm it is possible to find clusters in this vector space. By assigning a label to each cluster according to the *manual* scoring of the respective codebook vectors, we achieve a (*semi*-) automatic detection of the sleep stages using the EEG. The method in essence only searches for 'similar' segments and thus no a priori rules need to be incorporated, leaving the final decision

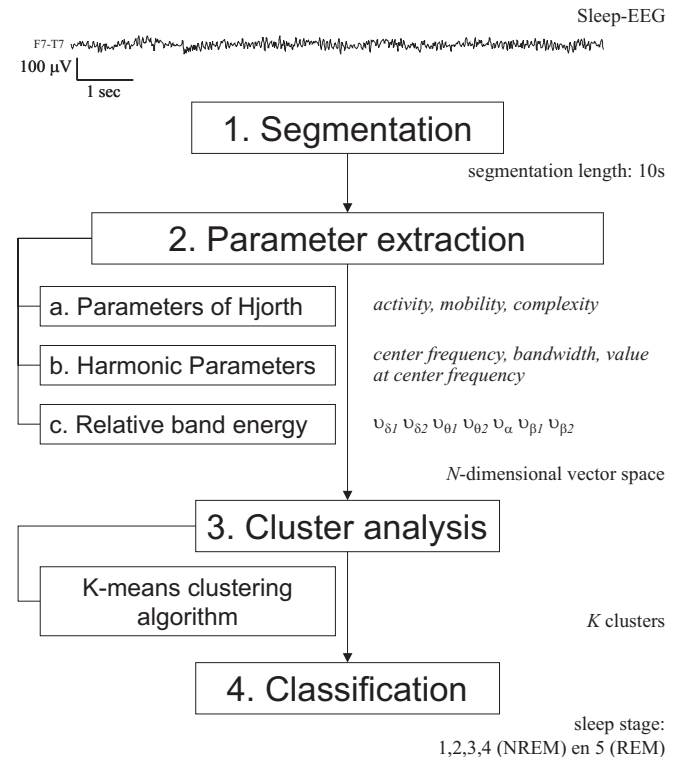


Figure 1. Schematic overview of the algorithm.

to the human reviewer.

2. METHOD

The method we developed consists of 4 consecutive steps, as depicted in figure 1: segmentation; parameter extraction; cluster analysis; and classification. Three sets of parameters were compared: the parameters of Hjorth, the harmonic parameters and the relative band energy. The cluster analysis was performed by using the K-means clustering algorithm.

2.1. Segmentation

In the segmentation step, one channel of the sampled EEG, $x[n]$, is broken down into sections with a fixed length, called segments. We choose the segment length to be 10s because we had the complete scoring for a sleep EEG in steps of 10s.

Report Documentation Page

Report Date 15 Oct 2002	Report Type N/A	Dates Covered (from... to) -
Title and Subtitle Automatic Detection of Sleep Stages Using the EEG		Contract Number
		Grant Number
		Program Element Number
Author(s)		Project Number
		Task Number
		Work Unit Number
Performing Organization Name(s) and Address(es) Elis Department MEDISIP, IBITECH, Ghent University, Belgium		Performing Organization Report Number
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500		Sponsor/Monitor's Acronym(s)
		Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited		
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.		
Abstract		
Subject Terms		
Report Classification unclassified	Classification of this page unclassified	
Classification of Abstract unclassified	Limitation of Abstract UU	
Number of Pages 4		

2.2.1. Parameters of Hjorth

Based on the variance of the signal $x[n]$ and its first and second derivative (differences) in a segment, Hjorth derived 3 parameters, sometimes called descriptors, for the quantification of an EEG. If we write the variance of the i -th derivative of $x[n]$ as σ_i (with σ_0 being the variance of $x[n]$), then the parameters of Hjorth are defined as follows [4]:

$$\text{Activity } A = \sigma_0^2 \quad (1)$$

$$\text{Mobility } M = \frac{\sigma_1}{\sigma_0} \quad (2)$$

$$\text{Complexity } C = \sqrt{(\sigma_2/\sigma_1)^2 - (\sigma_1/\sigma_0)^2}. \quad (3)$$

It is possible to relate these parameters to the moments of the spectral density function $S_{xx}(f)$ [5], showing that *mobility* is a measure for the center frequency and that *complexity* is a measure for the bandwidth of the signal.

It is also shown that the parameters of Hjorth give a valid description of an EEG only if the signal has a symmetric probability density function with only one maximum. It must also be noted that the accuracy by which the parameter *complexity* can be computed is limited. This is due to the fact that one must calculate the first and second derivatives and take the ratio between them and thus one possibly amplifies the noise. Therefore, to reduced the influence of high noise frequencies, one should band filter the EEG.

Nonetheless, these parameters can be valuable in a practical analysis if the EEG patterns to be analysed have a simple character, e.g., sleep recordings, and because the parameters can be easily computed from the time signal [5].

Calculation of the parameters of Hjorth for every segment results in a 3 dimensional vector space.

2.2.2. Harmonic parameters

Using an estimate of the spectral density function $S_{xx}(f)$, the harmonic parameters [6] are the center frequency, the bandwidth and the value at the center frequency, defined as follows:

$$f_c = \frac{\int_{f_L}^{f_H} f S_{xx}(f) df}{\int_{f_L}^{f_H} S_{xx}(f) df}, \quad (4)$$

$$f_\sigma = \sqrt{\frac{\int_{f_L}^{f_H} (f - f_c)^2 S_{xx}(f) df}{\int_{f_L}^{f_H} S_{xx}(f) df}}, \quad (5)$$

$$S_{f_c} = S_{xx}(f_c). \quad (6)$$

These parameters are calculated using the spectral density function between f_L and f_H , thus allowing to investigate a specific band in the EEG, instead of the whole EEG spectrum. The spectral density function $S_{xx}(f)$ was estimated using the method of Welch [7].

2.2.3. Relative band energy

Using 7 predefined frequency bands, the relative band energy is defined as the ratio between the energy in a band to the total energy. The 7 bands we used are given in table 1, in accordance with [8].

Table 1. Definition of 7 energy bands

Band	range (Hz)
Delta 1	0.5–2.5
Delta 2	2.5–4
Theta 1	4–6
Theta 2	6–8
Alpha	8–12
Beta 1	12–20
Beta 2	20–45

2.3. Cluster analysis

The goal in cluster analysis is to categorize (cluster) a number of points into K groups or clusters so that the *distortion*, i.e. the within-cluster sum of distances between member points and the centroid (also called the *codebook vector*), is minimized. In general, it is not possible to find an analytical solution that results in an optimal global minimum. Therefore, one uses an algorithm that guarantees at least to find a local minimum.

We used a slightly modified version of the K-means algorithm [9] to find the clusters and corresponding codebook vectors. In the *basic* K-means algorithm one starts with K initial codebook vectors and these are iteratively adjusted until a (local) minimum is found. The final result is, however, very sensitive to the selection of the initial codebook vectors. In our implementation, the *modified* K-means algorithm, we start with only 2 initial codebook vectors and apply the basic K-means algorithm to obtain 2 good codebook vectors. Then we iteratively increase the number of clusters until the desired number K is reached by dividing the greatest cluster (the cluster who's within-cluster sum of distances between member points and the centroid is greatest) into 2 new clusters and applying the K-means algorithm again.

It is also important to mention that we choose the so-called mini-max centre as a codebook vector of a cluster instead of the centroid. The mini-max centre is the point in cluster who's maximal within-cluster distance, is minimal. As a result we always obtain codebook vectors that correspond to a segment of the EEG.

We choose K equal to 20, and afterwards reduced the number of clusters to 5 (number of sleep stages) by grouping some clusters so that non-spherical clusters could be modeled.

2.4. Classification

The final step is classification. Every point (corresponding to a segment of the EEG) in a cluster, is scored according to the (manual) scoring of the segments corresponding to the constructed codebook vectors. The classification in sleep stages of the whole EEG thus only requires the manual scoring of 20 segments.

3. RESULTS

To verify the method we applied the algorithm to one 6-hour sleep EEG recording. Twenty-one electrodes were placed according to the international 10-20 system, with six additional lateral electrodes to cover the temporal regions. The sleep EEG had been visually scored by an experienced neurologist in steps of 10s.

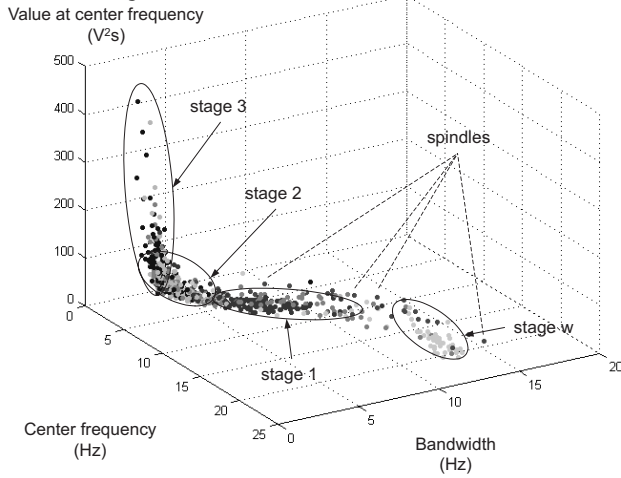


Figure 2. The vector space constructed with the harmonic parameters for the channel F7-T7.

The algorithm as described above was applied to the channel F7-T7 for the 3 sets of parameters. The resulting vector space for the harmonic parameters is depicted in figure 2 and this for the first 2 hours of the EEG. The results with the 2 other sets of parameters, the parameters of Hjorth and the relative band energy, are very similar. The regions (clusters) corresponding to the different sleep stages (as visually scored) are indicated.

Figure 2 shows that stage *w* (awake) and stage 1 can be clearly distinguished. The clusters corresponding to stage 2 and stage 3 are somewhat overlapping, hence making the automatic detection harder. However, it should be noted that even experienced neurologists have difficulty in classifying the different stages without using extra information (e.g., ECG and EOG). Furthermore, automatic detection of the sleep stages is complicated by the presence of so-called sleep spindles, short waveforms (2–3 s) with a frequency of 12–14 Hz. The parameter vectors associated with these spindles are scattered in the constructed vector space.

Figure 3 shows the 20 clusters found in the vector space obtained after cluster analysis with the modified K-means algorithm. Note that the different parameters had to be normalized prior to the application of the clustering. In figure 4 the final classification is depicted. As suspected, sleep spindles are not being correctly classified due to the fact that the K-means algorithm searches for spherical clusters. We suggest altering the method so that in a first step the spindles are being detected and in a second step the detection of the sleep stages follows, without taking into account the segments containing a detected spindles.

4. CONCLUSION AND DISCUSSION

The parameters we investigated, the parameters of Hjorth, the harmonic parameters and the relative band energy, are capable of extracting relevant information from the EEG usable for sleep stage classification. However, it should be noted that extra information (e.g., ECG and EOG) is needed for a

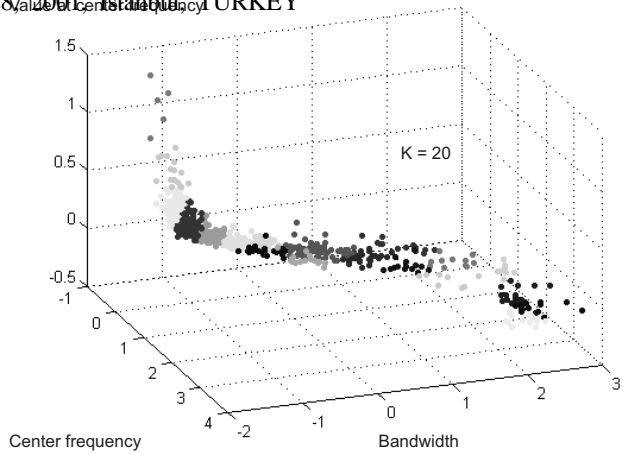


Figure 3. The constructed vector space after cluster analysis with the k-means algorithm.

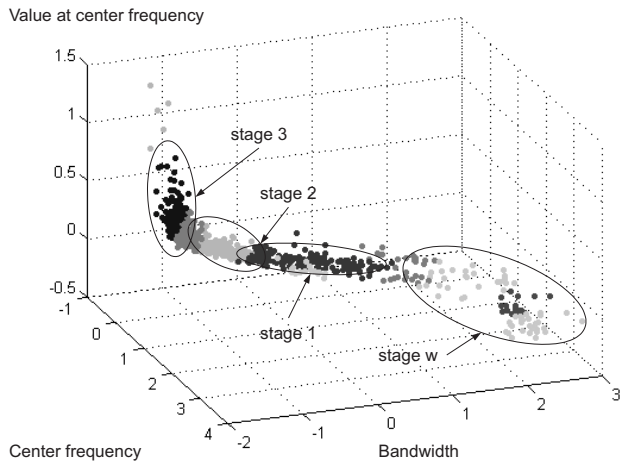


Figure 4. The constructed vector space after classification of the clusters.

clear discrimination between the different sleep stages. Probably the method will perform better if the information contained in all the channels is being used. In addition, the method has to be validated using the EEG from different patients.

The use of contextual information can probably enhance the agreement between the classification obtained by the algorithm and the visual scoring of the expert. Instead of trying to mimic the classification of the expert, our method essentially searches for ‘similar’ segments in the EEG. By presenting the representative segments of the EEG we leave the final decision to the neurologist.

5. ACKNOWLEDGEMENT

REFERENCES

- [1] A. Rechtschaffen and A. Kales, *A manual of standardized terminology, techniques and scoring system for sleep stages of human subjects*, 1968.

- [2] F. De Carli, F. Ferrillo, M. Gabarra, and G. Rosadini, "Waveform Analysis and Adaptive Classification in a System for Automatic Sleep Staging," in *Analysis of the Electrical Activity of the Brain*, pp. 253–259, John Wiley & Sons Ltd., 1997.
- [3] E. Stanus, B. Lacroix, M. Kerkhofs, and J. Mendlewicz, "Automated sleep scoring: a comparative reliability study of two algorithms," *Electroencephalography and clinical Neurophysiology*, pp. 448–456, 1987.
- [4] B. Hjorth, "Time domain descriptors and their relation to a particular model for generation of EEG activity," in *CEAN - Computerized EEG Analysis* (G. Dolce and H. Künkel, eds.), pp. 3–8, Gustav Fischer Verlag, Stuttgart, 1975. Symposium of Merck'sche Gesellschaft für Kunst und Wissenschaft Kronberg/Taunus, April 8th–10th, 1974.
- [5] F. Lopes da Silva, "EEG analysis: Theory and practice," in *Electro-encephalography, Basic Principles, Clinical Applications and Related Fields*, ch. 53, pp. 871–897, Urban & Schwarzenber, 1987.
- [6] K. Donohue and C. Scheib, "EEG fractal response to anesthetic gas concentration." www.engr.uky.edu/~donohue/eeg/pre1/EEGpre2.html.
- [7] J. Proakis and M. D.G., *Digital Signal Processing*, ch. 12. Power Spectrum Estimation. Prentice-Hall, Inc., 1996.
- [8] F. Lopes da Silva, "Computer-assisted EEG diagnosis: Pattern recognition techniques," in *Electro-encephalography, Basic Principles, Clinical Applications and Related Fields*, ch. 54, pp. 899–919, Urban & Schwarzenber, 1987.
- [9] X.D. Huang, Y. Ariki and M.A. Jack, *Hidden Markov Models for Speech Recognition*, ch. Vector Quantisation and Mixture Densities, pp. 111–119. Edinburgh University Press, 1990.